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**APPLICATION FOR UNITED STATES
LETTERS PATENT**

SEMANTIC LANGUAGE MODELING AND CONFIDENCE MEASUREMENT

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SEMANTIC LANGUAGE MODELING AND CONFIDENCE MEASUREMENT**BACKGROUND****1. Field of Exemplary Embodiments**

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Aspects of the invention relate to language modeling, and more particularly to systems and methods which use semantic parse trees for language modeling and confidence measurement.

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2. Description of the Related Art

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Large vocabulary continuous speech recognition (LVCSR) often employs statistical language modeling techniques to improve recognition performance. Language modeling provides an estimate for the probability of a word sequence (or sentence) $P(w_1 w_2 w_3 \dots w_N)$ in a language or a subdomain of a language. A prominent method in statistical language modeling is n-gram language modeling, which is based on estimating the sentence probability by combining probabilities of each word in the context of previous n-1 words.

Although n-gram language models achieve a certain level of performance, they are not optimal. N-grams do not model the long-range dependencies, semantic and syntactic structure of a sentence accurately.

5 A related problem to modeling semantic information in a sentence is the confidence measurement based on semantic analysis. As the speech recognition output will always be subject to some level of uncertainty, it may be vital to employ some measure that indicates the reliability of the
10 correctness of the hypothesized words. The majority of approaches to confidence annotation methods use two basic steps: (1) generate as many features as possible based on speech recognition and/or a natural language understanding process, (2) use a classifier to combine these features in
15 a reasonable way.

There are a number of overlapping speech recognition based features that are exploited in many studies (see e.g., R. San-Segundo, B. Pellom, K. Hacioglu and W. Ward, "Confidence Measures for Spoken Dialog Systems", ICASSP-
20 2001, pp. 393-396, Salt Lake City, UT, May 2001; R. Zhang and A. Rudnicky, "Word Level Confidence Annotation Using Combination of Features", Eurospeech-2001, Aalborg, Denmark, Sept., 2002; and C. Pao, P. Schmid and J. Glass,

"Confidence Scoring for Speech Understanding Systems",
ICSLP-98, Sydney, Australia, Dec. 1998). For domain
independent large vocabulary speech recognition systems,
posterior probability based on a word graph is shown to be
5 the single most useful confidence feature (see, F. Wessel,
K. Macherey and H. Ney, "A Comparison of Word Graph and N-
best List Based Confidence Measures", pp.1587-1590, ICASSP-
2000, Istanbul, Turkey, June 2000). Semantic information
can be considered as an additional information source
10 complementing speech recognition information. In many, if
not all, of the previous studies the way the semantic
information is incorporated into the decision process is
rather ad hoc. For example in C. Pao et al., "Confidence
Scoring for Speech Understanding Systems", referenced
15 above, the semantic weights assigned to words are based on
heuristics. Similarly, in P. Carpenter, C. Jin, D. Wilson,
R. Zhang, D. Bohus and A. Rudnicky, "Is This Conversation
on Track", Eurospeech-2001, pp. 2121-2124, Aalborg,
Denmark, Sept. 2001, such semantic features as "uncovered
20 word percentage", "gap number", "slot number", etc. are
generated experimentally in an effort to incorporate
semantic information into the confidence metric.

SUMMARY

A system and method for speech recognition, includes a unified language model including a semantic language model and a lexical language model. A recognition engine finds a
5 parse tree to analyze a word group using the lexical model and the semantic models. The parse tree is selected based on lexical information and semantic information, which considers tags, labels, and extensions to recognize speech.

Preferred methods may be integrated into a speech
10 recognition engine or applied to lattices or N-best lists generated by speech recognition.

A method for speech recognition includes generating a set of likely hypotheses in recognizing speech, rescoring the likely hypotheses by using semantic content by
15 employing semantic structured language models, and scoring parse trees to identify a best sentence according to the sentence's parse tree by employing the semantic structured language models to clarify the recognized speech.

In other embodiments, the step of determining a
20 confidence measurement is included. The confidence measurement determination may include includes employing a statistical method to combine word sequences with a parser tree to determine a confidence score for recognized speech. This may include determining the confidence measurement by
25 employing scores obtained from the semantic structured

language models along with other speech recognition based features. The scores may be obtained by extracting probabilities assigned to tags, labels and extensions obtained from a parser tree. The step of combining the semantic structured language models and speech recognition based features with the extracted probabilities using a classifier may be included

These and other objects, features and advantages of the present exemplary systems and methods will become apparent from the following detailed description of illustrative embodiments thereof, which is to be read in connection with the accompanying drawings.

BRIEF DESCRIPTION OF DRAWINGS

The exemplary embodiments will be described in detail in the following description of preferred embodiments with reference to the following figures wherein:

FIG. 1 is a block diagram showing a speech recognition and confidence measurement system in accordance with the present disclosure;

FIG. 2 is a diagram showing an illustrative parse tree employed to recognize speech and further shows information (e.g., w_{j-2} , w_{j-1} , L_i , O_i , N_i and M_i) obtained from the parse tree to build a semantic language model in accordance with the present disclosure;

FIG. 3 is a diagram showing an illustrative classifier tree with probabilities assigned employed to provide confidence scores in accordance with the present disclosure; and

5 FIG. 4 is a block/flow diagram showing a speech recognition and confidence measurement method in accordance with the present disclosure.

10 **DETAILED DESCRIPTION OF PREFERRED EMBODIMENTS**

The present disclosure provides a system and method, which incorporates semantic information in a semantic parse tree into language modeling. The semantic structured language modeling (SSLM) methods may employ varying levels
15 of lexical and semantic information using any of the statistical learning techniques including, for example, maximum entropy modeling, decision trees, neural networks, support vector machines or simple counts. In one
embodiment, maximum entropy modeling is used. This
20 embodiment will be employed as an illustrative example herein.

In accordance with this disclosure, a set of methods is based on semantic analysis of sentences. These techniques utilize information extracted from parsed sentences to statistically model semantic and lexical content of the sentences. A maximum entropy method is employed, for example, to rescore N-best speech recognizer hypotheses using semantic features in addition to lexical features.

The maximum entropy method (MEM) may be used for language modeling in the context of n-grams, sentence-based statistical language modeling and syntactic structured language models. However, an exemplary embodiment of the present disclosure employs MEM to incorporate semantic features into a unified language model. This integration enables one to easily use semantic features in language modeling. Semantic features can be obtained from a statistical parser as well as from a stochastic recursive transition network (SRTN). These features encode information related to the semantic interpretation of each word and word groups, which is one important consideration to distinguish meaningful word sequences from less meaningful or meaningless ones.

It should be understood that the elements shown in the FIGS. may be implemented in various forms of hardware, software or combinations thereof. Preferably, these elements are implemented in software on one or more
5 appropriately programmed general-purpose digital computers having a processor and memory and input/output interfaces.

Referring now to the drawings in which like numerals represent the same or similar elements and initially to FIG. 1, a system 100 for carrying out one embodiment is
10 shown. System 100 may include a computer device or network, which provides speech recognition capabilities. System 100 may be employed to train speech recognition models or may be employed as a speech recognition system or speech analyzer. System 100 may include an input device
15 for inputting text or speech to be recognized. Input device 102 may include a microphone, a keyboard, a mouse, a touch screen display, a disk drive or any other input device. Inputs to input device 102 may include semantic information, which can be stored in memory 105. This
20 semantic information may be employed to construct semantic language models 108 in accordance with the present disclosure.

Semantic information is employed in a semantic parse tree to be used in language modeling. The semantic structured language modeling (SSLM) methods or programs stored in language models 106 and semantic language model 108 may employ varying levels of lexical and semantic information using any of the statistical learning techniques including, for example, maximum entropy modeling, decision trees, neural networks, support vector machines or simple counts. This method may be carried out be employing a speech recognition engine or engines 104.

Speech recognition module 104 processes acoustic input, digital signals, text or other input information to recognize speech or organize the input to create language models 106, semantic language models 108 or other programs or databases 110, such as vocabularies, dictionaries, other language models or data, etc. Engine 104 may provide speech recognition capabilities for system 100 by employing any known speech recognition methods.

In accordance with this disclosure, engine 104 also employs a set of methods based on semantic analysis of sentences to enhance the speech recognition capabilities of system 100. These techniques utilize information extracted from parsed sentences to statistically model semantic and lexical content of the sentences. A maximum entropy method is employed, for example, to rescore N-best speech recognizer hypotheses using semantic features in addition to lexical features.

The maximum entropy method (MEM) may be used for language modeling in the context of n-grams, sentence-based statistical language modeling and syntactic structured language models. MEM is illustratively employed as an exemplary embodiment in the present disclosure to incorporate semantic features into a unified language model 107. This integration enables easy usage of semantic features in language modeling. Semantic features can be obtained from a statistical parser as well as from a stochastic recursive transition network (SRTN), which may be incorporated in module 104.

These parsing features encode information related to the semantic interpretation of each word and word groups, which is one important consideration to distinguish meaningful word sequences from less meaningful or meaningless ones.

Semantic information may include one or more of word choice, order of words, proximity to other related words, idiomatic expressions or any other information based word, tag, label, extension or token history.

5 This semantic information is employed to develop language modeling by training a model 108 based on the semantic information available. These models may include the following illustrative semantic structured language models (SSLM).

10 **MELM1 (Maximum Entropy Method 1)** preferably uses unigram, bigram and trigram features. It is possible to use more intelligent features that will capture a longer range and higher-level information. Considering data sparsity and
15 computation requirements, the following sublist of context question types for individual token probability computations may be employed (see MELM2).

20 **MELM2 (Maximum Entropy Method 2)** uses longer-range semantic features, for example, 7 types of features:

Unigram: (default question)

bigram: previous word w_{j-1} (ignore label tokens)

trigram: two previous words w_{j-1} and w_{j-2} (ignore label tokens)

Current active parent label Li (parent constituent label)

Ni (number of tokens to the left since current L starts)

Oi (previous closed constituent label)

Mi (number of tokens to the left after Oi finishes)

5 7 types of questions: (default), (wj-1), (wj-1, wj-2),
(Li), (Li, Ni), (Li, Ni, wj-1), (Oi, Mi)

Note that, these are the questions are chosen for the
maximum entropy (ME) model. There may be many other
possible features that utilize other information such as
10 tags, grandparent labels etc. The choices could be
dependent on the domain or the type of semantic parsing
employed. The maximum entropy framework enables one to
incorporate any type of features as long as they are
computable.

15 The model 108 is employed to calculate word
probabilities to decipher probabilities that particular
word sequences or phrases have been employed.

Referring to FIG. 2, an example application of MELM2
to compute $P(t_i = \text{for} | \text{history})$ is presented as a parser
20 tree.

The probability of the token sequence, [!S! I want to
book a [RT-OW one way RT-OW] ticket to [LOC Houston Texas
LOC] for [DATE tomorrow DATE] [TIME morning TIME] is

equivalent to joint probability of a classer tree and the word sequence given as the following equation:

$$P(W,C) \approx \prod_{i=1} P(t_i | t_1, \dots, t_{i-3}, t_{i-2}, t_{i-1})$$

Where a token t can be a word, label, tag, etc.

5 Another SSLM includes **MELM3 (Maximum Entropy Method 3)**, which combines semantic classer and parser and uses a full parse tree 150. The full parse tree 150 presents a complete semantic structure of the sentence where, in addition to classer information, such as RT-OW (round-trip
10 one way), LOC (location), DATE, TIME, semantic relationships between the constituents are also derived, e.g., $wj-2$, $wj-1$, t_i . The following features are used to train a Maximum Entropy based statistical model:

15 7 history parameters of MELM3

$wj-1$: previous word $wj-1$ (ignore label tokens)

$wj-2$: previous word of previous word (ignore label tokens)

L : (parent constituent label)

N : (number of tokens to the left since L starts)

20 O : (previous closed constituent label)

M : (number of tokens to the left after O finishes)

G: (grandparent label)

6 history question types: (default), (wj-1), (wj-1, wj-2),
(L,N), (O,M), (L,G)

5 Although the trees that the questions are based on are
different, MELM2 and MELM3 share similar questions. Indeed,
only the fifth question of MELM3 is not included in the
MELM2 question set. Note that even though these specific
question sets are selected for MELM2 and MELM3, any
10 question based on classer and parser trees can be a
legitimate choice in Maximum Entropy modeling.

 The inventors experimentally determined that these
question sets performed adequately in training a language
model. Inclusion of additional questions did not
15 significantly improve the performance for the
illustratively described task.

 The set of semantic language modeling techniques,
MELM1, MELM2 and MELM3 improve speech recognition accuracy.
In addition, features derived from these language models
20 can be used for confidence measurement by employing
confidence measurement module 112 (FIG. 1).

 Module 112 uses the language model score for a given
word in MELM2 model, which is conditioned not only on

previous words but also tags, labels and relative coverage of these labels over words. Tags define the types of words regarding their semantic content. For example, the tag assigned to Houston is "city". Words that are not
5 semantically important are assigned a "null" tag. Labels are used to categorize a word or word group into one of the concepts. The number of labels is less than the number of tags. An extension or arc is the connection between a tag assigned to a word and the label. Relative coverage refers
10 to how far the current word is from the beginning of the current label.

MELM2 presents an effective statistical method to combine word sequences with a semantic parse tree. Therefore, the MELM2 score, for example, may be used as a
15 feature for confidence measurement. However, MELM2 for a given word only depends on the previous word sequence and the parse tree up to that word. A low score can be expected for the current word if the previous word is recognized incorrectly. Besides the MELM2 score for the
20 current word w_i , a window of three words ($[w_{i-1} \ w_i \ w_{i+1}]$), MELM2-ctx3, were considered and five words, MELM2-ctx5, centered on the current word to capture the

context information. The same features can be derived for MELM3 as well.

Referring to FIG. 3 with continued reference to FIG. 1), probabilities obtained by module 104 from semantic
5 parse trees stored in model 108 can also be used for confidence measurement in module 112. The classer/parser performs a left-to-right bottom-up search to find the best parse tree for a given sentence. During the search, each tag node (tag), label node (e.g., LOC) and extension (ext)
10 in the parse tree is assigned a probability. Similarly, an extension probability represents the probability of placing that extension between the current node and its parent node given the "context". When the parser is conducting the search both lexical (from model 106) and the semantic clues
15 (from model 108) are used to generate the best parser action.

The degree of confidence while assigning the tag and the label feature values is reflected in the associated probabilities. If the word does not "fit" in the current
20 lexical and semantic context, its tag and labels are likely to be assigned low probabilities. Therefore, using these probabilities as features in the confidence measurement is a viable way to capture the semantics of a sentence.

Below is the classer tree for the phrase "from West Palm Beach Florida". The corresponding classer tree is shown in FIG. 3. cTag (shown as "tag" in FIG. 3) and cTagExt (shown as "ext" in FIG. 3) are classer tag and tag extension probabilities, respectively. Likewise in a parser tree, as opposed to a classer tree, "arc" and "ext" would correspond to pTag and pTagExt, which are parser tag and tag extension probabilities, respectively.

A classer tree 160 is shown in FIG. 3 along with its text representation. Each token has a pair of probabilities.

```
{0.502155 {!S!_1_1 :LOC_dmfeedback_1_0.997937
from_word_0.99371_0.995734 {LOC_0.999976_0.998174
west_city_0.635543_0.894638 palm_city_0.998609_0.981378
beach_city_0.998609_0.957721 florida_state_0.96017_0.995701
LOC_0.999976_0.998174} !S!_1_1} }
```

Confidence measurements by module 112 are optional, but can greatly improve speech recognition accuracy, which is output in block 114. Output 114 may be customized to any form. For example, output 114 may be speech synthesized and

acoustically rendered, textually render, transmitted as an analog or digital signal, etc.

The following are some specific examples where SSLM corrects errors committed by regular n-gram methods. These
5 examples were run by the inventors to show the advantages of the present embodiment using MEM. Confidence scores are also given below to show improvements.

Reference (Ref): **new horizons and and blue chip**

10 n-gram: log is an end **blue chip**

sslm: **horizons and and blue chip**

Ref: **what is my balance by money type**

n-gram: **what** was the of my **money sent**

15 sslm: **what is my balance by money take**

Ref: **change pin**

n-gram: **change** plan

sslm: **change pin**

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The following are some specific examples where errors committed by posterior probability features are corrected by the semantic confidence features. The threshold for

confidence is set to 0.87, which roughly corresponds to 5% False Acceptance rate for both posterior probability (post) and sslm+post (sslm and posterior probability). These examples are correctly accepted by sslm+post features but
5 falsely rejected by the post features alone:

Ref: balance

Hypothesis (Hyp): balance

10 Post: 0.54 (confidence measure)

Post+sslm: 0.95 (confidence measure)

Ref: summary

Hyp: summary

15

Post : 0.63 (confidence measure)

Post+sslm: 0.93 (confidence measure)

Ref: plan

20 Hyp: plan

Post: 0.79 (confidence measure)

Post+sslm: 0.88 (confidence measure)

The following examples are correctly rejected by
sslm+post features but falsely accepted with post features
alone:

5

Ref: call
Hyp: <SIL>

post_conf: 0.88 (confidence measure)
10 post+sslm: 0.04 (confidence measure)

Ref: -
Hyp: have

15 post_conf: 0.93 (confidence measure)
post+sslm: 0.82 (confidence measure)

Ref: representative
Hyp: rep

20

post_conf: 0.88 (confidence measure)
post+sslm: 0.70 (confidence measure)

Referring to FIG. 4, a method for speech recognition includes providing or training a language model in block 202. The language model may be trained using known training techniques, such as n-gram, CFG, etc. In block 5 204, input to be recognized is received. The input may be in any form permitted by the speech recognition method or device. In block 206, one or more speech recognition methods may be employed to generate a set of likely hypotheses. The hypotheses are preferably in the form of 10 an N-best list or lattice structure.

In block 208, semantic structured language models (SSLM) are employed to rescore the likely hypotheses based on the semantic content of the hypotheses. This is performed by evaluating the hypothesis using the SSLM 15 models, e.g., MELM2 or MELM3, etc. In block 210, parse trees are scored to identify a best sentence in accordance with its parse tree. This is performed by using SSLMs trained in accordance with history parameters and history questions to further clarify the speech recognized.

20 The history parameters may include a previous word (w_{j-1}), a previous word of the previous word (w_{j-2}), a parent constituent label (L), a number of tokens (N) to the left since L starts, a previous closed constituent label

(O), a number of tokens (M) to the left after O finishes, and a grandparent label (G). The history questions may include a default, (wj-1), (wj-1, wj-2), (L,N), (O,M), and (L,G).

5 In block 212, a confidence measurement or score may be determined by employing the scores obtained from the SSLM along with other speech recognition based features, e.g., posterior probability, etc. In block 214 probabilities assigned to tags, labels, extensions, etc. obtained from
10 the parser tree may be combined with SSLM and speech recognition based features using a classifier. These probabilities may be employed to further improve speech recognition by increasing the level of confidence in confidence scores.

15 Having described preferred embodiments for semantic language modeling and confidence measurement (which are intended to be illustrative and not limiting), it is noted that modifications and variations can be made by persons skilled in the art in light of the above teachings. It is
20 therefore to be understood that changes may be made in the particular embodiments disclosed which are within the scope and spirit of the present disclosure as outlined by the appended claims. Having thus described the exemplary

embodiments with the details and particularity required by the patent laws, what is claimed and desired protected by Letters Patent is set forth in the appended claims.